NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

DEEP LEARNING CLASSIFICATION OF BUILDING TYPES IN NORTHERN CYPRUS

MUBARAK AHMAD MUHAMMAD

M.Sc. THESIS

Nicosia

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Approval

We certify that we have read the thesis submitted by **Mubarak Ahmad Muhammad** titled "**Deep learning classification of building types in northern Cyprus "** and that, in our combined opinion, it is fully adequate, in scope and quality, as a thesis for the degree of **Master of Science in Electrical and Electronics Engineering**

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Acknowledgements

First and always, I would thank God for giving me the strength to finish this work. Semesters has passed; I had some good days, and other hard days, whenever I was down, God has always given me hope and strength to continue. This thesis would not be done without the support and patience of my supervisor Prof. Dr. Sertan Serte for his constant encouragement and guidance. They had guided me through all the stages of the writing of my thesis. Without their consistent and illuminating instruction, this thesis could not have reached its present form.

Thanks are due to all the staff and Management, Faculty of Electrical and Electronics Engineering Department, NEU. My sincere appreciation also extends to all my family members especially my Father, Mother, and my brothers for their understanding and encourage me all the time until complete on this research project.

I am also indebted to the librarians at Near East University (NEU) for their help in supplying the relevant literature, and lastly, I wish to express my sincere appreciation to all the people that assisted throughout the preparation for this Thesis.

To my parents…

Abstract

Among the areas where AI studies centered on developing models that provide real-time solutions for the real estate industry are real estate price forecasting, building age, and types and design of the building (villa, apartment, floor number). Nevertheless, within the ML sector, DL is an emerging region with an Interest increases every year. As a result, a growing number of DL research are in conferences and papers, models for real estate have begun to emerge. In this research, we present a method called deep learning method for classification of houses in Northern Cyprus using Convolutional neural network

The classification will be based on the house age, house price, number of floors in the house, house type i.e. Villa and Apartment.

The first category is Villa versus Apartments class, the second category is split into two class according to age of the buildings, namely 0 to 5 years Apartments 6 to 10 years Apartments. This class is to classified the building based on their age and. The third category is villa with roof versus Villa without roof apartments class The fourth category is Villa Price from 10,000 euro to 200,000 Versus Villa Price from 200,000 Euro to above. The last category consists of three classes namely 2 floor Apartment versus 3 floor Apartment, 2 floor Apartment versus 4 floor Apartment and 2 floor Apartment versus 5 floor Apartment.

From the experiments carried out in this thesis, the accuracy, sensitivity and specificity were recorded for all the classes and from the results obtained we conclude that the main aims and objectives of this thesis was achieved. This study will be very significant in creation of smart cities and digitization of real estate sector as the world embrace the used of the vast power of new emerging technology i.e. Artificial Intelligence and Machine Vision.

Keyword: AlexNet; Northern Cyprus; Convolutional Neural Network; Apartment; Villa; Deep learning.

Özet

Yapay zeka çalışmalarının gayrimenkul sektörü için gerçek zamanlı çözümler sunan modeller geliştirmeye odaklandığı alanlar arasında gayrimenkul fiyat tahmini, bina yaşı ve bina türleri ve tasarımı (villa, daire, kat numarası) yer alıyor. Bununla birlikte, ML sektöründe, DL her yıl Faiz artışı ile yükselen bir bölgedir. Sonuç olarak, artan sayıda DL araştırması konferanslarda ve bildirilerde yer alıyor, emlak için modeller ortaya çıkmaya başladı. Bu çalışmada, Kuzey Kıbrıs'taki evlerin Evrişimli sinir ağı kullanılarak sınıflandırılması için bir derin öğrenme yöntemi sunuyoruz.

Bu çalışma, ev görüntülerinin sınıflandırılmasında Evrişimli sinir ağlarının kullanımını önermektedir. Sınıflandırma, evin yaşı, konut fiyatı, evdeki kat sayısı, ev tipi, yani Villa ve Daire'ye göre yapılacaktır.

Birinci kategori Villa vs Apartments sınıfı, ikinci kategori binaların yaşına göre iki sınıfa ayrılır, yani 0 ila 5 yıl Daireler 6 ila 10 yıl Daireler. Bu sınıf binayı yaşlarına göre sınıflandırmak ve. Üçüncü kategori ise çatılı villaya karşı Villa çatılı daireler sınıfı Dördüncü kategori ise 10.000 Euro'dan 200.000 Versus Villa Price'a 200.000 Euro'dan üzeri villa fiyatı. Son kategori üç sınıftan oluşur, yani 2 kat Daire ve 3 kat Daire, 2 kat Daire ve 4 kat Daire ve 2 kat Daire ve 5 kat Daire.

Bu tezde yapılan deneylerden tüm sınıflar için doğruluk, duyarlılık ve özgüllük kaydedilmiş ve elde edilen sonuçlardan bu tezin temel amaç ve hedeflerine ulaşıldığı sonucuna varıyoruz.. Dünya Yapay Zeka, makine öğrenimi ve makine vizyonunun muazzam gücünün kullanımını kucakladığından, bu çalışma akıllı şehirlerin yaratılması ve gayrimenkul sektörünün sayısallaşması açısından çok önemli olacak.

Anahtar Sözcükler: Derin öğrenme, AlexNet, Evrişimli Sinir Ağı, Kuzey Kıbrıs, Apartman, Villa

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LIST OF ABREVIATIONS

AI:	Artificial Intelligence
ML:	Machine Learning
DL:	Deep Learning
CNN:	Convolutional Neural Networks
TRNC:	Turkish Republic of Northern Cyprus
ANN:	Artificial Neural Networks
SVM:	Support Vector Machine
GI:	Gastro Intestine
GDP:	Gross Domestic Product
RBM:	Restricted Boltzmann Machine
DNN:	Deep Neural Network
RNN:	Recurrent Neural Network
GPU:	Graphical Processing Unit
GRU:	Gated Recurrent Unit
LTSM:	Long Short-Term Memory
GAN:	Generative Adversarial Network

CHAPTER 1
INTRODUCTION

For each economy in the world, the importance of real estate statistics is undisputed and widely accepted. The drivers of demand and the availability of prices for real estate vary across nations. Such drivers depend on various variables that can alter over time. The real estate market is, indeed, competitive and it can be a challenge to recognize a complete list of drivers. However, it may not be practical for researchers to include an extensive description of factors.(Gilani, 2020).

While Northern Cyprus is just a nation that cover the northeastern side of Cyprus Island, but only Turkish Government recognizes it., it attracted a number of tourists and students. Many stakeholders, such as government agencies, families, investors, financial institutions and others, are interested in the housing market, making the results of this thesis important.

The Ottoman era (1571-1878) was significant for the architecture of housing in the Island. Examples of houses belonging to that old time and is still there presently(Kiessel et al., 2011).

In the last few years, construction of buildings have increased dramatically after a failed peace plan initiated in 2003 by UN Secretary-General(Kiessel et al., 2011). Ever since, Northern Cyprus's architectural design has shown a strong tendency towards post-moderation. The creation of Northern Cyprus' modern architecture is inspired from improvements since about the 1980s in Turkey and by Turkish designers who have not been officially recognized for their job. The buildings types in Northern Cyprus are mostly Villa, residence or apartment, penthouse, bungalow.

Among the areas where AI studies centered on developing models that provide real-time solutions for the real estate industry are real estate price forecasting, building age, and types and design of the building (villa, apartment, floor number). Nevertheless, within the ML sector, DL is an emerging region with an Interest increases every year. As a result, a growing number of DL research are in conferences and papers, models for real estate have begun to emerge. In this study, our emphasis is to provide an approach using deep learning for classification of houses in Northern Cyprus.

As a machine learning technique, deep learning emulates the function of the human brain after analyzing the given datasets to make a human-like decision. Deep learning is an algorithm that uses artificial multi-layer neural networks to learn the characteristics of unstructured data correlation. It retrieves the functionality using raw data in the form of regression and or classification(Arulkumaran et al., n.d.).

To boost the level of computer vision, the utilization of the deep learning approach of the CNN in image classification is praised worldwide. Using training algorithms, deep learning can identify the input datasets and allow the computer to classify or identify the image depending on the form of training.

This Thesis proposes the utilization of CNNs in building types classification using houses images. The classification will be based on the house age, house price, number of floors in the house, house type i.e. Villa and Apartment. For this reason, database of the houses images is collected and going to be used with our system.

1.1 Aim

As the world embrace the used of the vast power of Artificial Intelligence and machine vision, the thesis main aim is to used Deep learning in Classification and detection of houses in Northern Cyprus.

1.2 Objectives of The Study

- To classify and identify Villa and Apartment
- To classify and identify houses of age from 0-5 and 6-10

- To classify and identify houses of different prices
- To classify and identify 2 floor apartments versus 3 floor, 4 floor and 5 floors.
- To Test the performance of AlexNet on houses classifications

1.3 Scope of the study

The study focuses on classifying the images using one CNN architecture (AlexNet)

1.4 Limitation

- Other CNN architectures like GoogleNet and ResNet are not tested
- Comparison with the other models is also beyond the scope of this research

1.5 Significant of the Research

The outcome of this research on the building type is very important for many essential applications such as, real estate management, spatial marketing, visualization and smart cities.

1.6 Thesis Structure

The structure of the thesis is as follows:

- Chapter one: this is a general introduction of the thesis where the aims, objectives, scope of the study and limitation of thesis are explained.
- Chapter two is a detailed review of the artificial neural network and its working principles, in addition to its training algorithm including backpropagation learning technique. Moreover, this chapter discusses the deep learning in particular, convolutional neural network is discuss.
- Chapter three presents the dataset description and methodology of the
- Chapter four is also a discussion of the results obtained from the network training. In this chapter, the network performance parameters are discussed.
- Finally, chapter five is a conclusion and recommendations.

CHAPTER 2
LITERATURE REVIEW

1.7 Introduction

Among the areas where AI studies centered on developing models that provide real-time solutions for the real estate industry are real estate price forecasting, building age, and types and design of the building (villa, apartment, floor number). Nevertheless, within the ML sector, DL is an emerging region with an Interest increases every year. As a result, a growing number of DL research are in conferences and papers, models for real estate have begun to emerge. In this study, our emphasis is to provide an approach using deep learning for classification of houses in Northern Cyprus.

In recent decades, a tiny subset of Artificial Intelligence (AI), also referred to as Machine Learning (ML) has, since the 1950s, revolutionized many areas. A subfield of ML is Neural Networks (NN) that produced Deep Learning (DL). DL has been producing ever greater changes since its inception, exhibiting outstanding performance in almost every application domain. DL comprise of many layers from the input to the output layers that allow for the existence of many levels of non-linear pattern recognition units with deep architectures used for functional learning and classification of patterns(Schmidhuber, 2015).

Recent literature notes that a Hierarchy of concepts or attributes includes DL-based representation learning.

Most famous deep learning algorithms are focused on ANN, especially CNN, in this chapter, we are going to review the related work, study area, previous study of ANN, DL and CNN, also we will see the usage of this models on real estate.

1.8 Related Work

1.8.1 Building Classification

Although the building age, price and types of the building are significant parameter in the construction specifications, the information is not always accessible or complete. For the classification of the building type or detection of buildings age, few researches have been performed**.**

Along with other research efforts, Henn et al introduces a SVMs classifier, latest ML tool for semantic enrichment of coarse 3D city model (Henn et al., 2012).

Henn et al research automatically define the form of construction In LOD1 models with a building features , e.g. number of floors and many attributes of the local background e.g. to the proximity to school or distance by using SVM (Henn et al., 2012).

SVM are used for the selection roof model. Unlike standard approaches, classification based on supervised models are capable of integrating additional features that allow a substantial improvement in the accuracy of model selection(Henn et al., 2013).

Yan Li et al(Y. Li et al., n.d.) The method was introduced and evaluated by a new approach to direct forecasting of building age from Street View images of Google and its accurately forecast with DCNN. İn the research, they used different CNN Architectures which include DenseNet161, AlexNet, ResNet 18 and ResNet 50.(Y. Li et al., n.d.).

F. Biljeck et al(Sensing et al., 2017) The paper discusses the possibilities for Forecasting the construction age of buildings using random forest regression from other attributes. The purpose of the research is to find whether the age of buildings or the year of construction using 3D GIS and machine learning can be inferred.

1.8.2 Image Classification

Deep learning Researchers have used conventional neural networks to classify images and produce a good result.

Using Fundus images, Sertan Serte and Ali Serenar (Serte, 2019) presents a generalized DL model for glaucoma detection. Its trained and evaluated on several datasets and architectures, contrary to previous studies. The findings show that 80% of the time, the model is equal or better than previous work in the literature. They (Serener, n.d.) also introduces, using fundus images to detect early and advanced glaucoma automatically. The

ResNet-50 and GoogleNet CNN algorithms are trained and fine-tuned using transfer learning to classify. The suggested method also produces good result.

The modified AlexNet architecture used in this study(Shanthi & Sabeenian, 2019) to categorize the input fundus images. the performance of the updated AlexNet architecture is assessed based on the Performance Matrices. The images obtained in diabetic retinopathy stage 1, Healthy retina, diabetic retinopathy stage 2 and 3 from the Messidor dataset shows an accuracy of 96.6%, 96.2%, 95.6% and 96.6% respectively.

Another study (M. Li et al., 2020) presents an algorithm called DC-AL GAN (Deep convolutional generative adversarial network) for unsupervised representation learning. It is capable, even from difficult GBM datasets, of learning interpretable representations. AlexNet is an important part of the architecture, used to extract characteristics as a discriminator.

Udayan Birajdar et al used artificial intelligence CNN in their method to make the process of diabetic retinopathy detection and classification much simpler and faster. The proposed model uses AlexNet, a convolutional neural network architecture trained to reliably diagnose Diabetic Retinopathy with minimal effort based on the fundus image database(Birajdar et al., 2020).

With pre-trained AlexNet, transfer learning was used in the skin diseases classification in Hosny et al research. And using the most recent ISIC 2018 public dataset, the proposed approach was tested. On the basis of the results obtained, the researchers may conclude that the approach proposed proved successful in correctly classifying the skin lesions into 7 groups. Dermatofibroma, basal cell carcinoma Melanocytic nevus, actinic, Melanoma, keratosis, vascular lesion and benign keratosis are among these groups. The performance achieved for accuracy, specificity, sensitivity and precision are 98.70%, 99.27%, 95.60% and 95.06% respectively (Hosny, 2020).

1.9 Study Area

Northern Cyprus comprises of the north east portion of the Cyprus island. Turkish Republic of Northern Cyprus is its official name. The island only recognized by Turkey but international communities still considered both North and South to be one country(Robertson, 2013).

TRNC ranges from Morpho Bay to the west and to the top of the northeastern Karpass Peninsula. The village of Louroujina is its southernmost point. A United Nations-controlled buffer zone extends between South and North and separates the capital Nicosia on both parts(Alptekin & Erta\cs, 1993).

The country is comprized of 6 districts namely Lefkosa, Famagusta, Kyrenia, İskele, Lefke and Güzelyurt, as shown in fig 1 below. In 2016, the district of Lefke was formed after the split of the district of Güzelyurt.

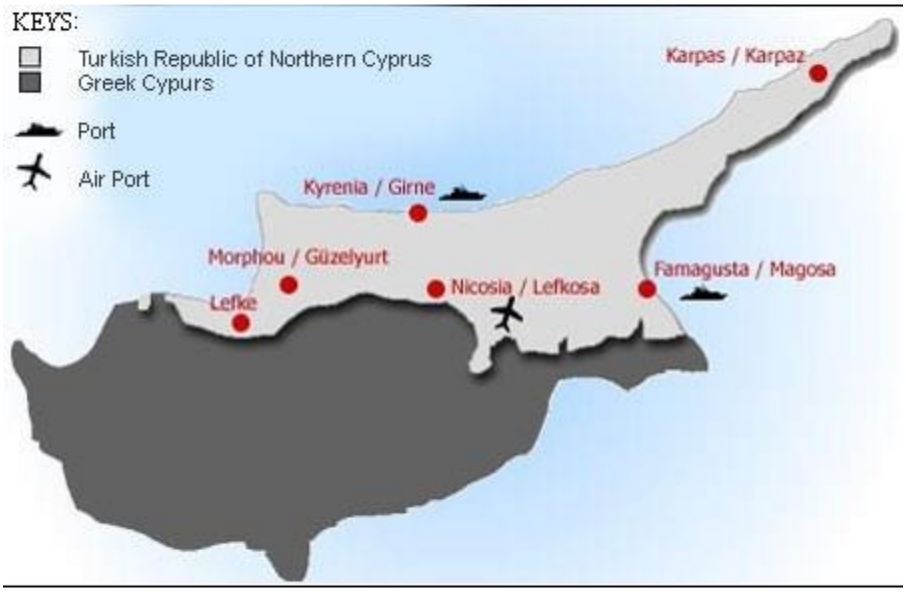

Figure 2.1: Map of Northern Cyprus(*North Cyprus Map*, n.d.)

There is an area of three thousand, three hundred and fifty five square kilometers in Northern Cyprus, while Turkey is seventy five kilometers (47 mi) north of Northern Cyprus and 97 kilometers (60.3 mi) east of Syria.

There are two bays on the Northern Cyprus coastline: Famagusta and Morphou Bay & 4 capes: Kormakitis, Apostolos, Kasa Andreas and Zeytin cape with the endpoint of the Karpaz Peninsula being Cape Apostolos Andreas. The narrow mountain range of Kyrenia flows along the coasts of the North, and Mount Selvili, This is where the highest point in north cyprus is 1,024-meter (3,360 ft) high mountain range(Alptekin & Erta\cs, 1993)(TIMBIL, 2003).

The driving economy in the country is considered to be tourism. The nation welcome over 1.1 million visitors in 2012, restaurants and hotels produced $328 million in revenue and accounted for 8.5% of GDP. (Prices, n.d.) In the same year, More than ten thousand jobs were created by accommodation and catering. In the 2000s and 2010s, the tourism sector saw great growthWith more than double the number of visitors, investment and hotel development increased(Akingbaso, 2014).

Northern Cyprus' third census results under the pretense of UN observers was carried out in 2011. A total population of 294,906 was recorded.(Akingbaso, 2014) Several political parties, trade unions and local newspapers challenged these results. Some claims that the Cyprus population has reached five hundred thousand(Cole, 2011),divided inbetween half of Turkish Cypriots and the other half of or Cypriot-born children of Turkish settlers. Another claims The overall population is expected to be 351,965 by the end of 2017.

The country is a democratic that combines different impacts and an economy controlled by service industryThe economy expanded in the last decade, but due to the official closing of the ports on the island by the international communities,There official language is Turkish. Muslims are the majority, though religious views are largely moderate and secular.

1.10 Machine Learning

ML is a subset of man-made brainpower that, based on this information, highlights AI for the most part from its experience and allows predictions. Described as data from training to build decisions to accomplish the task without precise programming(Burkov, n.d.).

AI calculation is prepared using a set of planning details to construct a model. It makes a prediction based on the model at the point where new data is familiar with an ML estimate. A machine learning application workflow begins with reading and observing the training data to discover valuable information and trends to construct a model that predicts the correct result. Using the test data collection, the efficiency of the model is then evaluated. This procedure is carried out until the computer automatically learns and maps the input to the correct output without any human action(Kumari, 2017).

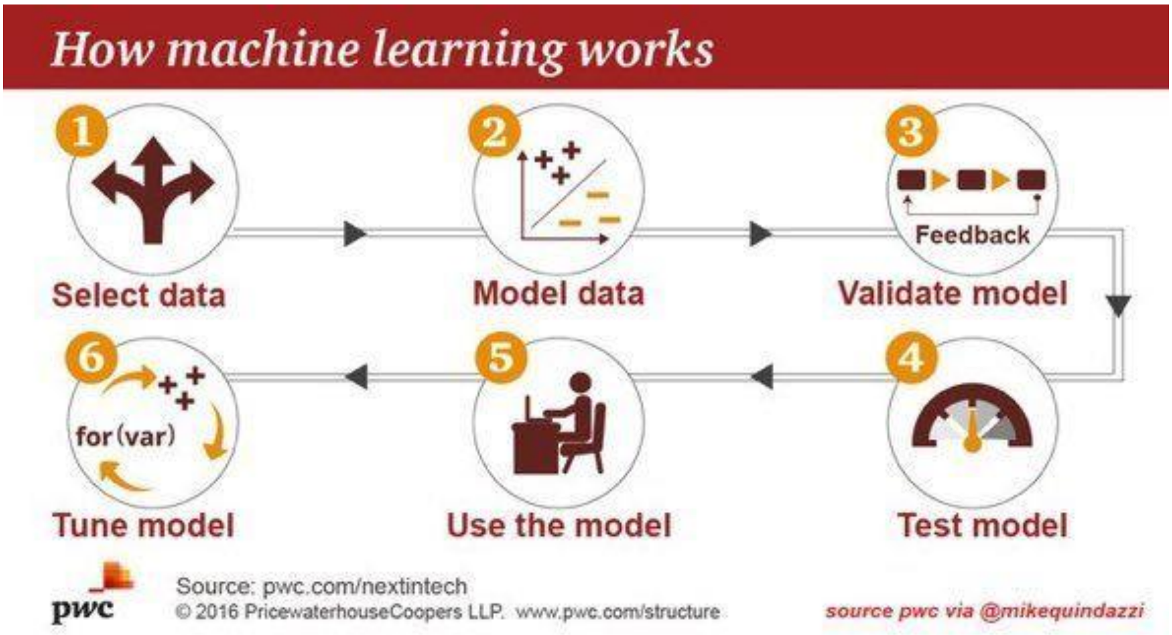

Figure 2.2 : Workflow of Machine Learning(Kumari, 2017)

1.11 Types of Machine Learning

Machine learning is subdivided into different kinds. Below are the four most relevant forms: supervised learning, unsupervised learning, semi-supervised and reinforcement and learning(Burkov, n.d.).

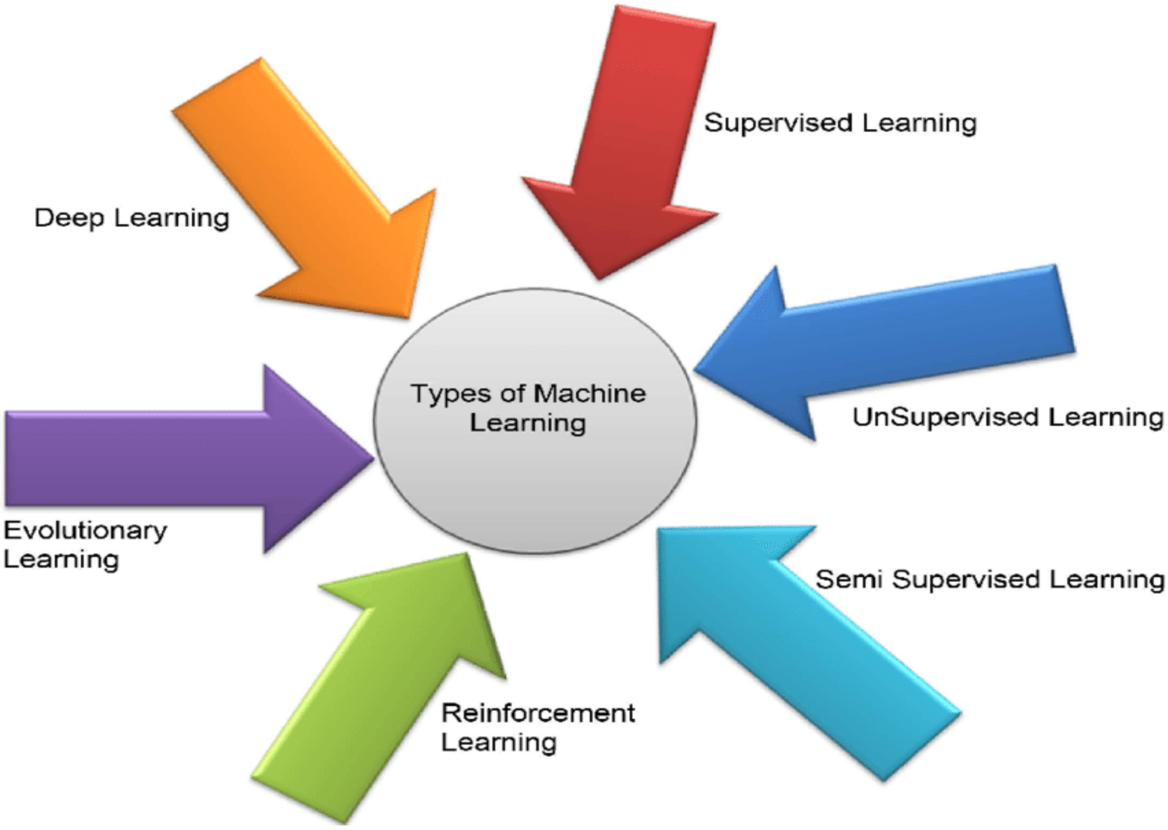

Figure 2.3: Types of ML(Burkov, n.d.)

1.11.1 Supervised Machine Learning

The dataset is the labeled set of supervised learning, where input variables (x), output variables (y) are used and the mapping function is learned from input to output to use an algorithm(Anandakumar & Umamaheswari, 2017).

$$f(x) = Y. \qquad 2.1$$

our objective, given a training set, is to define the supervised learning problem slightly more formally, to research a feature $h: x \rightarrow y$ so that $h(x)$ is an analyst for the value of y where h is the model. This function is called a hypothesis. It is seen basically like this below.

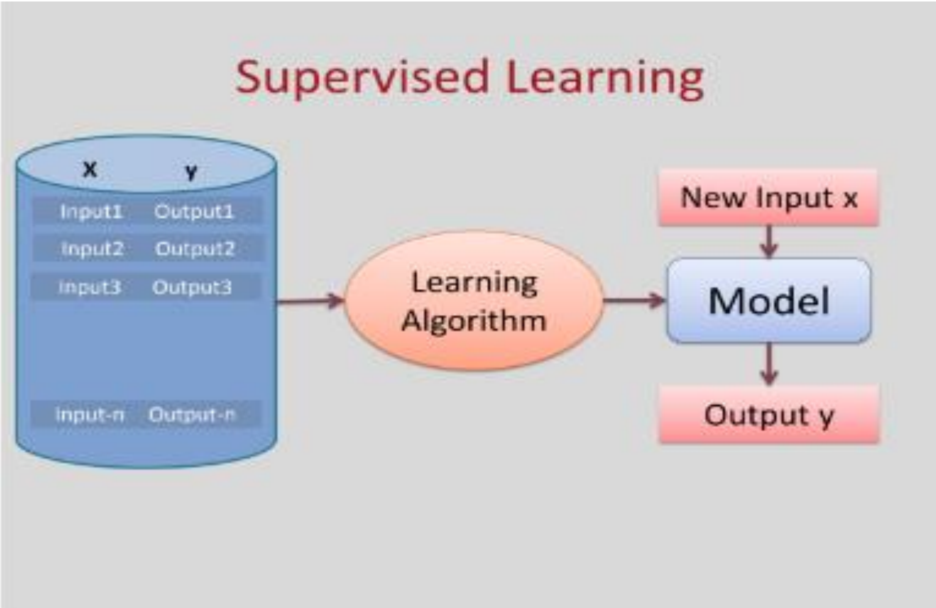

Figure 2.4: Mapping of Supervised Learning(Schmidhuber, 2015)

It is called the problem of learning a regression while attempting to predict the target variable is constant, as in a housing case. If only a small discrete value can be inferred by y.

It can be called a classification problem, such as provided the living area, to be predicted whether a building is said, a house or apartment.

Regression and classification can also be divided by supervised learning challenges. An issue with classification is when the category is the output variable, such as 'villa or apartment' or 'villa with roof or villa without roof.' A regression is if the output variable has a true value, such as "weight"(Schmidhuber, 2015).

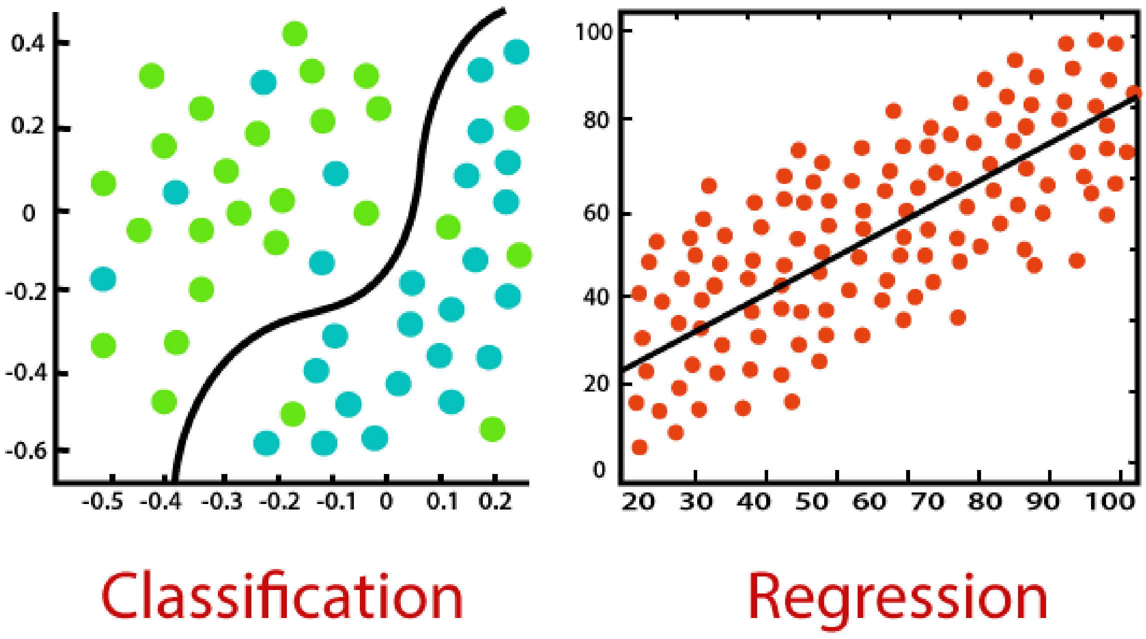

Figure 2.5: Classification and regression models(Uçar et al., 2017)

1.11.2 Unsupervised Machine Learning

In this class, effects are distinctively categorized with conceptual conditions in this form of machine learning and non-marked or supervised learning is the area in which there is no dependent variable.

The first thing in this method is to start with the points as individual clusters as it moves forward, there is only one cluster in each stage in Marge the nearest cluster pair. Three forms of unknown data without labels in that method have no clear information set during unsupervised learning, and most of the issues are largely unidentified(Burkov, n.d.).

In easy terms, the AI system and ML target are blinded as the process goes, the system has immense and faultless logical operation to direct it along the way, but the availability of sufficient input and output algorithms makes the system much more complicated. Amazing as the complete system sound, unsupervised learning is able to interpret and seeking an answer to an infinite number of data, through input data and the process of binary logic current in all computer systems. There is no reference data in the model.

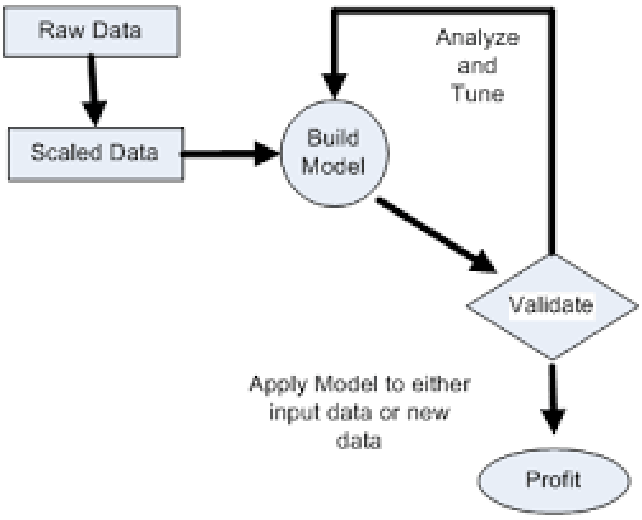

Figure 2.6: Workflow of Unsupervised Learning(Schmidhuber, 2015)

1.11.3 Semi Supervised Learning

This is a learning paradigm which examines how machines and natural systems, such as how human beings learn when knowledge is explicitly labeled and unlabeled. In this unsupervised learning model like clustering where all the information is unlabeled, either learning has historically been studied, the aim Semi-supervised learning is about knowing why and how the combination of unlabeled and labeled information will alter learning and design algorithms for us.

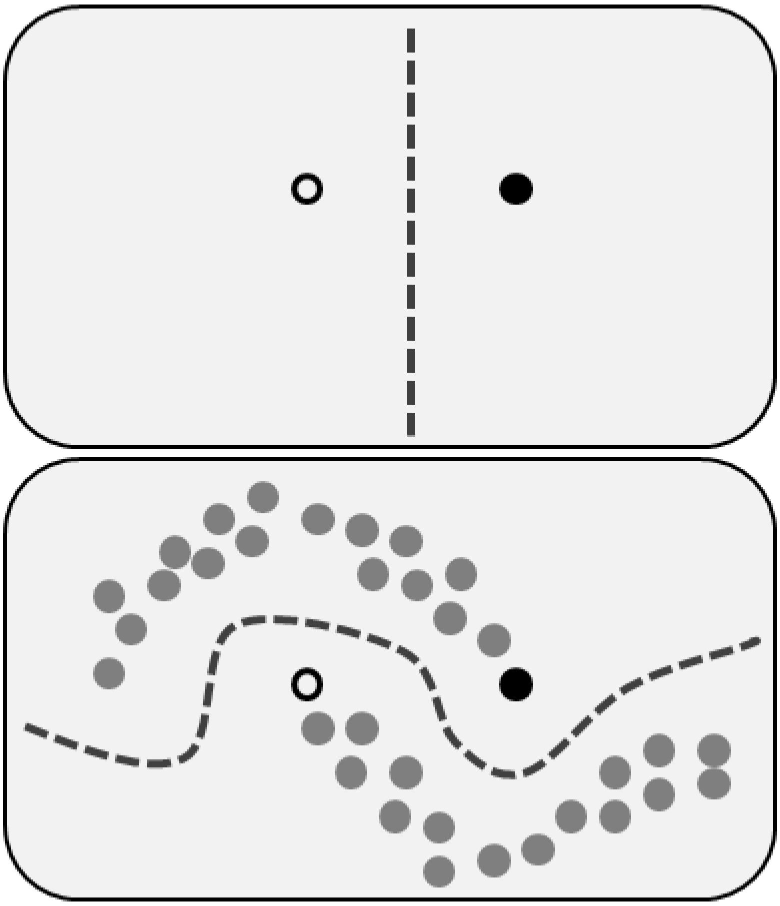

Figure 2.7: Semi Supervised Machine Learning(Schmidhuber, 2015)

An instance in semi-supervised learning, the effect of unlabeled data. The panel at the top demonstrates a number of options that could be made after having just one negative example of a black dot, one positive white dot. In addition to the two labeled instances, the bottom panel shows a decision boundary that could be Chosen to take if a set of black dots of unlabeled data were given. This could be seen as clustering and then categorizing the labeled information on the clusters, pushing the decimal boundary(Zengul, 2019).

1.11.4 Reinforcement Machine Learning

In reinforcement learning, the agent is an intelligent program that is the initial segment and decision maker. The surrounding area is the setting that has the objective of the agent to execute. To analyze the environment, an internal state is maintained by an agent. Actions that are the tasks carried out by the agent in the setting, incentives used to train agents(Krittanawong et al., 2017)

While there is no right answer in reinforcement learning, the agent decides what correct response to fulfill the giving mission. It is sure to benefit from its experience without the training dataset.

Reinforcement learning is related to five elements.

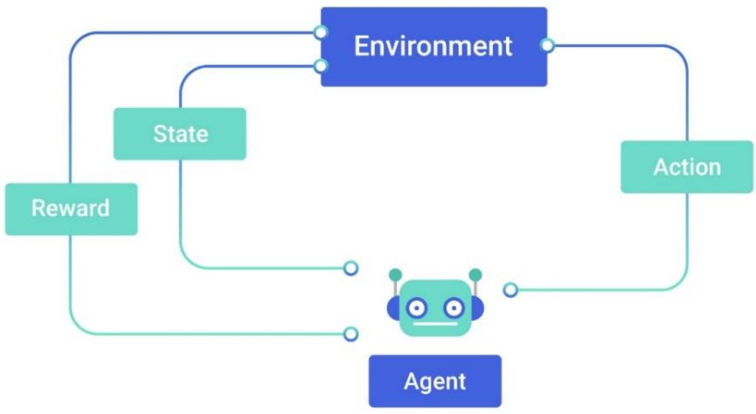

Figure 2.8: Workflow of Reinforcement learning(Burkov, n.d.)

1.12 Artificial Neural Network

Artificial neural networks are mechanisms used for thinking that derive from the cerebrum of the human brain. The system has been used to deal with problematic science problems. The vast majority of neural system structures are like the organic mind in the need to plan before having the ability to perform the necessary task. There are many aspects that ANN imitates the brain. Information storage and system management is performed in a way very close to that in the brain. Over many years ANN applications in other diverse fields are a testament to their importance, even beyond engineering(Kumari, 2017)

Despite the learning technique, the framework of ANNs comprises three layers. The layers, weights, and capacities of initiation are these angles. In the ANN limit, every last one of these three parts plays an imperative lead. The three sections or segments work together to ensure the device performs properly(1 Introduction to Soft Computing 1.1, 2008).

A network structure with inputs $(x1,\ x2,\ \ldots\ xi)$, $(w1,\ w2\ldots\ wij)$ is shown in Figure 1 below.$Q(\cdot)$ is the AF and y_k and b_k is the output and bias which has effect in transformation and producing output y_k.

There is a weight attached to any relation that It can either have a positive or a negative meaning linked to it. The transfer function can be represented mathematically as follows(Alom et al., n.d.):

$$TP = \sum x_i \, w_{ij}$$ **Equation 2.2**

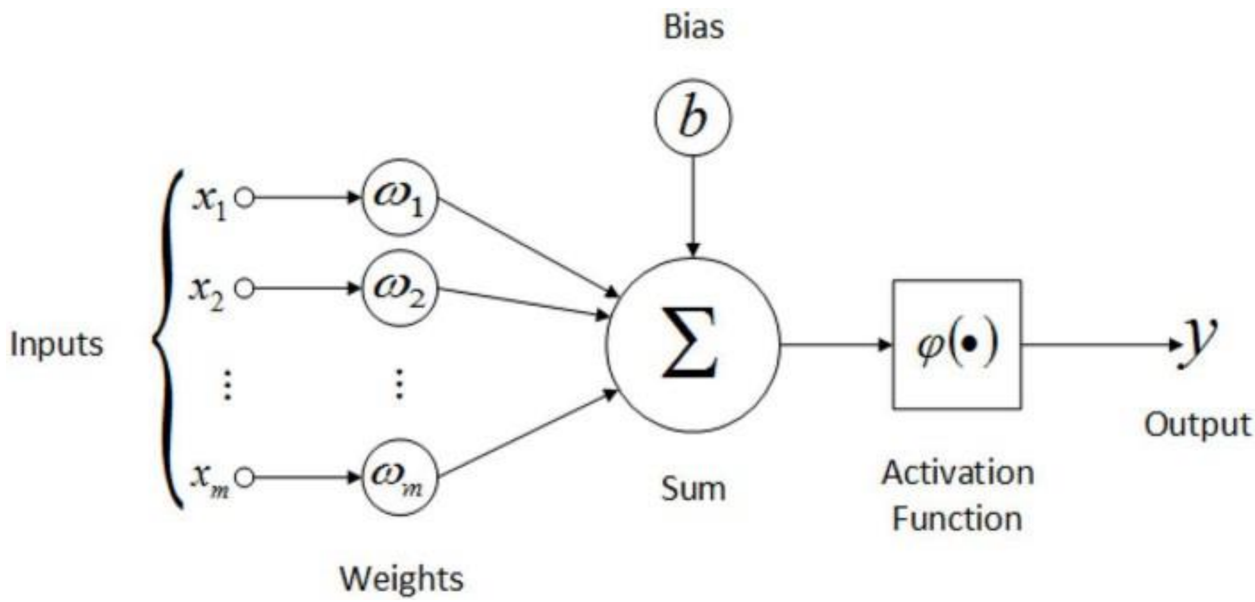

Figure 2.9: Artificial Neural Network structure(Ahire, n.d.)

The neuron is activated by positive weights, while negative weights inhibit it. The signals that it receives are summed up by the neuron, multiplying each signal on the link by its relevant weights. Then the output (y) which is transferred over a function of activation function $g(y)$, which give the final output $0j$. Because of its easily distinguishable properties, the sigmoid (logistic function) is the most widely used function, That is very useful when applying the algorithm for back-propagation (Burkov, n.d.)..

The weights are adjusted on each of the interactions between the neurons. Input information is then fed forward, creating another output and error until an effective reduced error is obtained, the procedure is reiterated. A transfer mechanism is used by each of the neurons and is entirely linked to nodes on the next layer. The training is stopped until the error exceeds an appropriate value(Ahire, n.d.).

1.13 ANN Layers

The key derivative of his inventions is the reciprocal interaction that exists between the layers of ANN. By sending data to each other using the synaptic weight, the layers interact. The structure of Ann can be subdivided into three layers, described in the following section below(Kumari, 2017).

1.13.1 Input layer

This is the first layer found in ANN's neural system. The layers that send information or data to other layers of the neural system are important. It can be regarded as sensors because information processed by other layers is not processed later, but only transferred

1.13.2 Hidden layer

This can be assumed to be the core part of the neural system. No less than one of the layers, which is input layer and neural layer, is involved. The layer transmits the data to the layers of the output. Since the synaptic weights found in it are reliable, the hidden layer can be seen as the intermediate layers or as a principal layer

.

1.13.3 Output layer

The output layers received its information that is processed from the Hidden layer in its last touch where the neural system results are obtained. The following figure describes the neural system and the relationships between its three layers.

1.14 Types of ANN

1.14.1 Fully connected

All the components are interconnected with one another. Each neuron's output is related to all others' inputs and its own inputs as shown in the figure below(Bystrov, n.d.).

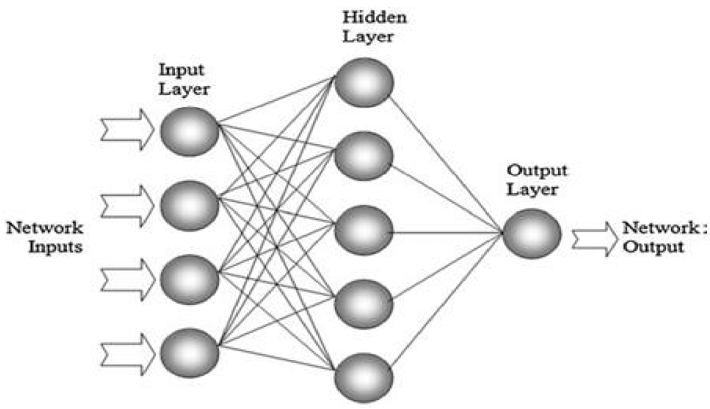

Figure 2.10: Fully connected neural network(burkov, 2004)

1.14.2 Hierarchical NN

Every neuron is connected with next and previous neuron as shown in the figure below(Bystrov, n.d.).

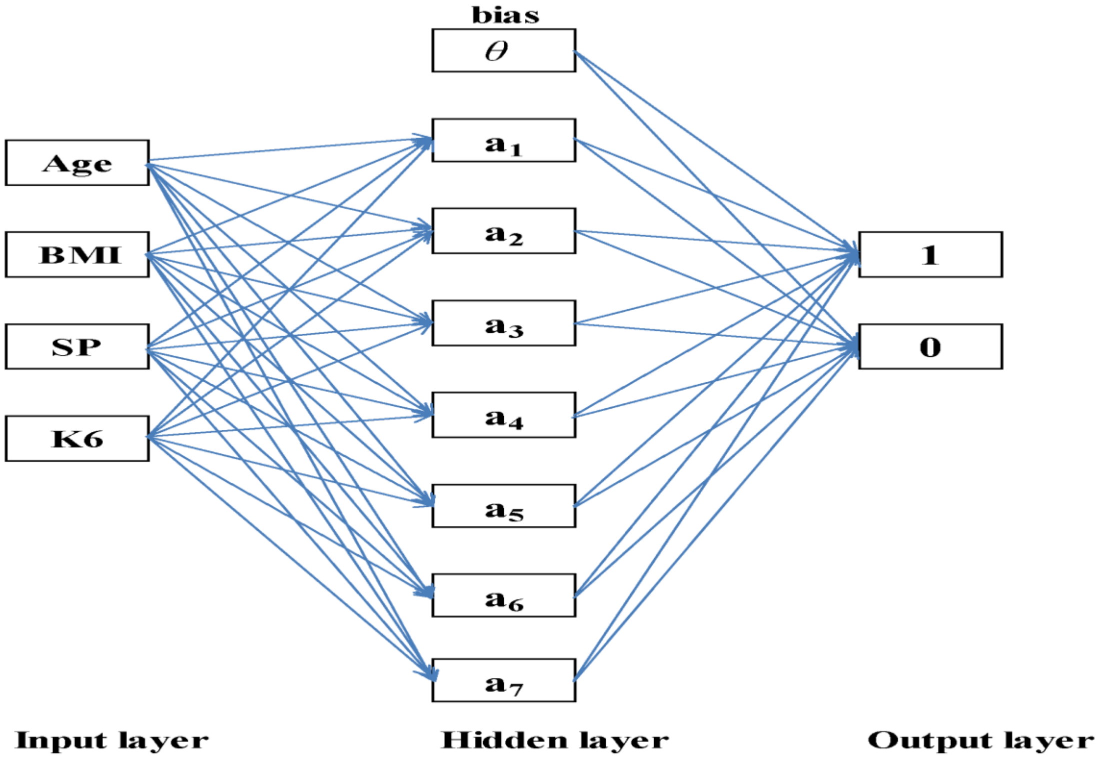

Figure 2.11: Hierarchical Neural Network(Bystrov, n.d)

1.14.3 Feed Forward NN

For this type of networks, neurons receive signals and transmit it to their outputs as shown in the figure below(Bystrov, n.d.).

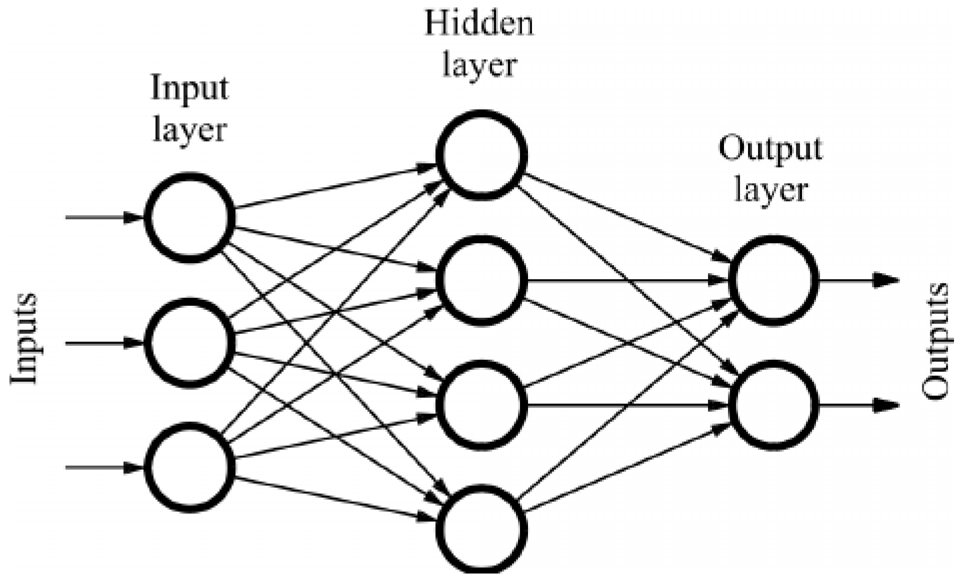

Figure 2.12: Feed forward Neural Networks(Velasco et al., 2019)

1.14.4 Feedback NN

This network is when the output signals from the higher layer are returned to the lower layer as input signals as shown in the figure below(Bystrov, n.d.)

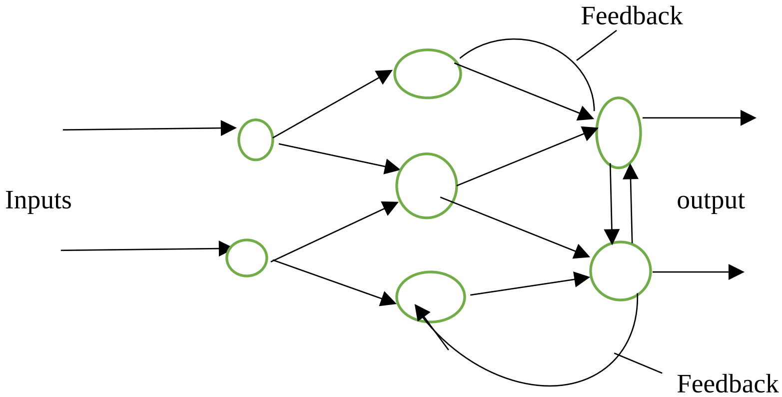

Figure 2.13: Feed backward Neural Network(Mohammadpour et al., 2018)

1.15 A Brief Description of ANN Parameters

1.15.1 Learning rate

This is a very important parameter in supervised learning; it is used to monitor how quickly the network learns training examples. The value of this parameter varies from 0 to 1. The learning rate specifies the step size by which the weights of the network are updated during training. If the value set for the learning rate is too high, there is a high probability that the network will only memorize the training data, as learning is done in lesser times, the Situation referred to as over-fitting(Santos et al., 2007).

$$n_t = \eta_o B^{t \div e} \qquad 2.3$$

Where n_t is the t^{th} learning rate, $\eta_o$is the initial learning rate, B is the decay factor with a range of values between $(0,1)$.

If the value set for the learning rate is too low, there is a risk that the network will not fail to learn the training data until the set number of maximum periods is reached. It follows that the use of a value that is too small for the learning rate makes learning much slower, and the network may not converge to the set MSE target until training is stopped.

The appropriate value for the learning rate is generally determined heuristically through the trial and error method. Low values are commonly favored

1.15.2 Momentum Rate

The momentum parameter is often optional for supervised learning, the sole purpose of which is to help reduce the ability of the network to be trapped at a poor local minimum during training. Its value also ranges from 0 to 1. The momentum rate parameter can be seen as a type of inertia being introduced into the network. It helps to drive past weak local minima through network preparation, and it also dampens the oscillations that may occur during learning, so the learning curve is usually smoother than when the momentum rate parameter is not used in the learning algorithm(Y ÜCEL İ NAN I, 2015).

$$v_t = \gamma_{vt-1} - \eta \nabla \mathrm{F}(\theta_{-1}) \quad 2.4$$

$$\theta_t = \theta_{t-1} + v_t \quad 2.5$$

Where the momentum is γ and the LR for the round t^{th} of the training is η.

The momentum values $[0,1]$. It's also observed its minimum is exceeded by a higher momentum value, potentially render it unpredictable for the network. Generally speaking, γ value is 0.5 before the learning is stabilized and then elevated to 0.9 or greater.

1.15.3 Maximum Epochs

Since neural networks learn from examples, the forward passing of an example from the input and the back of the computed error is what is referred to as an epoch. This process is repeated with each training example until all examples have been distributed across the network; then the process repeats in this way, while the fixed value for the MSE target is monitored(Bystrov, 2018).

In the training of neural networks, it is very important to determine the maximum amount of variables required in the learning. This has the effect of not allowing the network to continue training indefinitely in a situation where learning has not been compatible with the MSE target set, and is thus used as a significant stopping criterion in training(Pattern Invariance, Oyebade Kayode Oyedotun, 2015).

1.15.4 Number of hidden neurons

For the back spread neural network and most other networks, the network consists of at least three layers, i.e. the output layer, the hidden layer and the input layer.

The input layer is which the training examples are given to the network, the secret layer learns the features represented in the input, where the output layer enables the actual output of the network to be accessed. Also, the input layer neurons are non-processed, they are basically used to supply input features to the network.

The output layer in supervised learning enables an error to be computed in between desired output and the network's real output; and therefore, back spreads errors in the network for weight adjustment or tuning.

The hidden layer is very important, given that it is where the main knowledge representation of the features present in the training examples is achieved. It is therefore very important that a sufficient number of neurons be used throughout the input layer of the NN to ensure proper training of the task(Oyebade Kayode Oyedotun, 2015).

1.15.5 Activation function

AF are used to squash the output of artificial neurons within a certain range of values. It is intended that the output of the neurons should not be infinite. The weighted number of the inputs to the neurons is calculated, the value referred to as the total potential, which is then passed through the activation function(Y Ücel I Nan, 2015). Common functions of activation used in neural networks include Sigmoid, Linear, Log-Sigmoid, and Tan-Sigmoid.

During the design of neural networks, the form of application decides the activation function to be used for each layer of the network.

For real values problems such as regression tasks, the linear activation function is used, for classification tasks, output values are usually integers, and thus Log-Sigmoid or Tan-Sigmoid may be used.

1.15.6 Goal of cost function (MSE)

Generally, for any supervised learning algorithm, because the cost function relating to the variance, it follows that a given value should be minimized for the purpose of the cost function(Burkov, n.d.).

When the network reaches the specified value for the MSE goal, the network training will be stopped.

1.16 Deep Learning

In the literature of classic neural network, the theoretical roots of deep learning are well developed. But DL allows for the use of several layers and hidden neurons as shown in figure below(Schmidhuber, 2015), unlike more conventional use of NNs. A higher perceptual degree corresponds to any lower-dimensional projection. This high level of abstraction offers an automated collection of features that would otherwise require hand-crafted or personalized features.

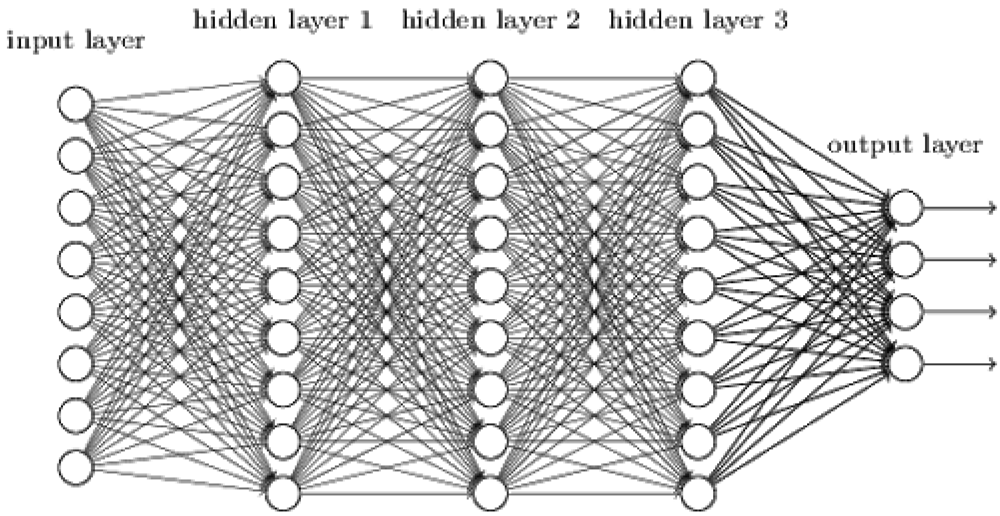

Figure 2.14: Deep Learning architecture(Schmidhuber, 2015)

The convolutional neural network deep learning architecture has a significant effect on image classification. Other possible DL architectures include some based-on constitution of RBMs such as DBNs, broadening ANN as DNNs with several layers or as Recurrent Neural Networks. Recent developments in GPUs have also had a substantial influence on deep learning's functional uptake and acceleration.

Deep learning architectures such as CNNs can be strongly implemented by forwarding the most popular algebraic activities with dense matrices such as matrix products and convolutions to the GPU. Until now, deep learning models for health informatics have been applied by a multitude of experimental works, achieving comparable output or surpass that of alternative methods in many cases (Vinayakumar et al., 2017).

In addition, extensive computational resources are needed for deep learning, which without it the training might become difficult. It can become an especially laborious job to solve to achieve a maximum description of the network's parameters.

NNs with one or more hidden layers of Perceptron have been implemented to solve more complex problems. Many stages or epochs are typically carried out to train these NNs where a new input sample is given based on the new learning method the weights of each neuro. Addition of hidden layers to the network enables the creation of a deep architecture that can communicate more complex theories as the nonlinear relationships are captured by the hidden layers. These Neural Networks are referred to as Deep Neural Networks.

Training Deep Neural Networks is not trivial since they become insignificant until the back-propagation of the errors are done on the first few layers, thus failing the learning process. While more advanced back propagation variants can get rid of the issue, they still lead to a very slow learning process.

New advanced methods for training deep learning architectures have been provided by deep learning. DNNs can, in general, learning for unsupervised and supervised learning strategies. Labeled information is used in supervised learning Training the DNNs and studying the weights that decrease the failure to determine a classification or regression target value, while training is done in unsupervised learning without having labeled data. For features extraction, reduction or clustering of dimensionality, unsupervised learning is typically used. It is popular for some applications to merge an actual DNN learning phase for an unsupervised learning step, the most important characteristics are extracted and then used for classification using a supervised learning step(Y Ücel I Nan, 2015).

Due to the increasing computational requirements, for processing and training, hardware limitations have made DNNs impractical for many years, for usage that involve real-time processing, in particular. Lately, hardware advancements have been partly overcome and DNNs have been recognized as a major advancement in artificial intelligence because of the possibility of GPU acceleration, cloud computing and multicore processing parallelization.

1.16.1 Deep Learning Approaches

1.16.1.1 Supervised Deep Learning

This types of learning used labelled input as described in chapter 1(Burkov, n.d.).

$$\{(x_i\,, y_i)\}_1^n = 1 \qquad 2.6$$

Each element x_i of N is referred to as feature vector of the function. A feature vector is the one in which every dimension$\mathrm{j} = 1 \ldots \mathrm{D}$ contains a value that defines the example. That value is called a feature and is labelled as $x(i)$. In this case $(xt, t){\sim}p$. To better estimate the desired outputs, the agent would then adjust the network parameters sequentially.

CNN, DNN and RNNs are various supervised learning methods. In this work, we are going to use CNN, therefore CNN is described in details.

1.16.1.2 Semi-Supervised Deep Learning

This type of Learning that takes place where the datasets is partly labeled and un labeled is semi-supervised learning. The objective of this learning algorithm is the same as the objective of the algorithm for supervised algorithm(Arulkumaran et al., n.d.). The idea here is that several unlabeled examples will be used to assist in seeking a better model with the learning algorithm. The algorithms that are used as semi-supervised methods of learning in some situations are Generative Adversarial Networks (GAN) and DRL. RNN is also used including LSTM and GRU.

1.16.1.3 Unsupervised Deep Learning

Unsupervised learning is the type of deep learning which effects are distinctively categorized with conceptual conditions in this form of deep learning and non-marked or supervised learning is the area in which there is no dependent variable. The agent in this case, discovers the internal representation or essential characteristics within the input data to discover unknown relationships or structures. unsupervised deep learning approaches include clustering, reduction of dimensionality and generative methods. Deep learning algorithms like, RBM, Auto Encoders (AE) and Generative Adversarial Network, uses clustering and reduction of dimensionality. In addition, RNNs are often used in many application domains for unsupervised learning, such as LSTM and RL(Burkov, n.d.).

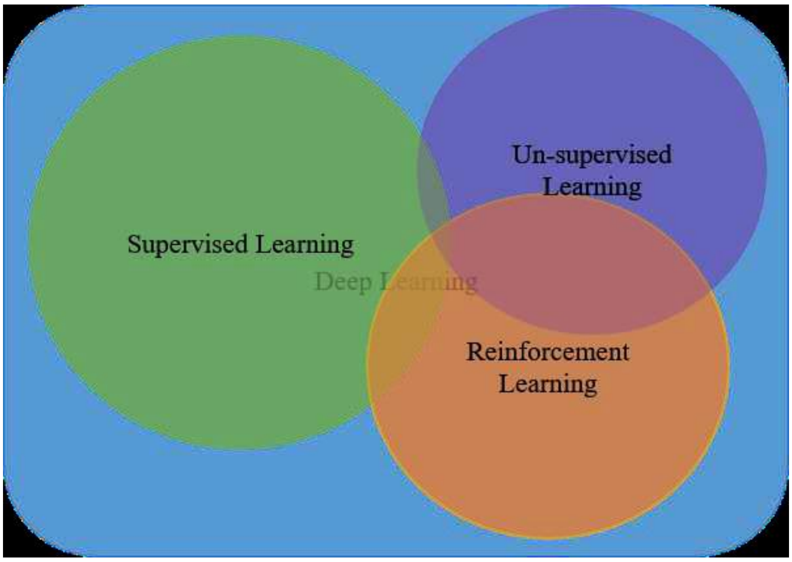

Figure 2.15:. Deep Learning Approaches types(Mnih et al., 2013)

1.16.1.4 Reinforcement Deep Learning

A learning strategy for use in unfamiliar settings is Deep Reinforcement Learning. DRL started with Google Deep Mind in 2013. Since then, many advanced RL-based approaches have been proposed. RL and SL have the following basic differences

- You must communicate with the functions.
- Interaction with a state-based environment feedback xt relies on past behavior (Mnih et al., 2013).

1.17 Convolutional Neural Network

Various architectures stand out in prominence among different methodological variants of DL. It shows the number of DL system publications since 2010. In particular, CNN had great achievement within the field of image classification. The design executing convolutional filters accompanied by decrease, reconfiguration of pooling layers. This architecture is biologically influenced by the mechanism in which the visual cortex embraces perceptual visual field(Springenberg et al., 2014)(Szegedy et al., 2015).

Fukushima first suggested this network structure in 1988 (Fukushima, 1988). However, it was not commonly used because of computer hardware limitations for network preparation. Researchers further enhanced CNNs after that and recorded outcomes in several tasks of detection. Convolutional Neural Networks have many benefits over Deep Neural Networks.

In absorbing shape variations, the CNN max pooling layer is successful. In addition, CNNs have substantially fewer parameters Constituted of feature connections with connected weights than a network of a similar scale that is fully connected. Along with gradient-based training algorithm, CNNs are trained and less affected by the decreasing the problem of gradient. CNN can generate substantial optimized weights by training the entire network to reduce an error criterion.

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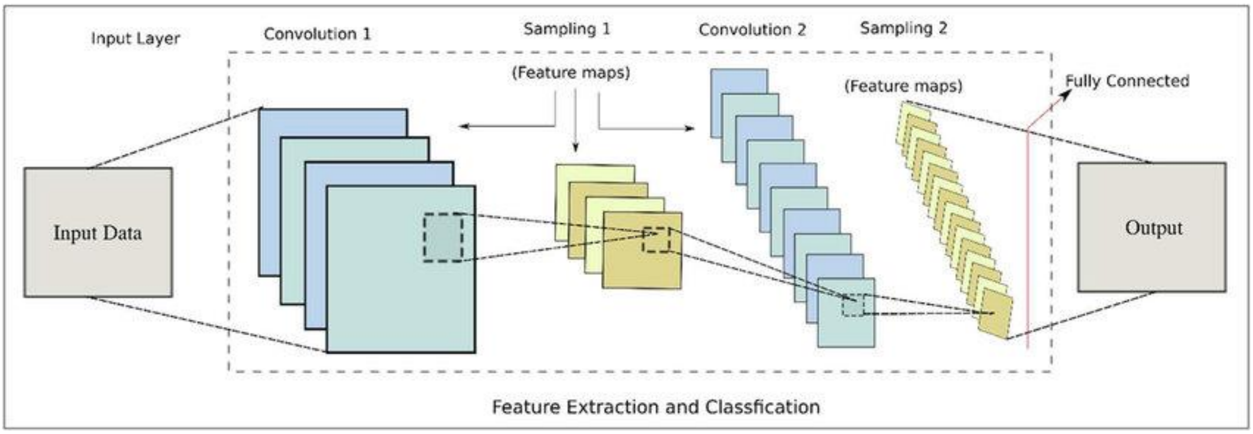

Figure 2.16: CNN General architecture(Kim et al., 2019)

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1.17.1 Convolution Layer

feature maps from preceding layer are combined with trainable kernels. The kernels output like hyperbolic tangent or identity functions to form a future map. We have that, in general,

$$x_j^l = f(\sum_{i \in Mj} x^{l-1} * k_{ij}^l + b_j^l) \qquad 2.7$$

Where x_j^l is the current layer's output

x_j^{l-1} is the output of the previous layer,

k_{ij}^l is the current kernel layer,

b_j^l is the current bias layer.

m_j is a set of input maps.

However, to produce the corresponding target maps, the source maps will be combined with separate kernels(Ozturk et al., 2020).

1.17.2 Sub-Sampling Layer

The down-sampled method is done by the subsampling layer. The amount of function maps for both input and the corresponding output does not change in this layer. Each output dimension for all the images will then be equal to half of the input dimension. You should formulate this operation as

$$x_j^l = down(x_j^{l-1}) \qquad 2.8$$

where $down$ is a sub-sampling function.

The function usually sums up the function maps from the previous layer over NXN patches Therefore, dimensions of the output map are therefore decreased. The output map of each layer is combined with a scalar in some special instances. Some alternate sub-sampling layers, like the convolution sub-sampling and fractional max-pooling and, have been proposed(Burkov, n.d.).

1.17.3 Classification Layer

Classification layer is a completely linked layer that in the preceding steps calculates each class performance from the obtained characteristics of a convolution layer. The output layer functions are defined as scalar vectors value that are transferred to the layers that are completely connected.

We don't have clear guidelines about the layer implemented in the network model. Meanwhile, in various architectures, like LeNet (LeCun et al., 1998), AlexNet(Krizhevsky & Hinton, n.d.), and VGG Net(Simonyan & Zisserman, 2014), two to four layers have been observed. Alternative methods have been suggested over the last few years (Omar et al., 2016).

1.18 CNN Architectures

We are now going to discuss some famous state-of-the-art CNN architectures. In general, a core collection of simple layers, including the convolution, dense, the sub-sampling, and the soft-max layers, make up deepest convolutional neural networks. Usually, the architectures consist of many max-pooling and convolution layers, accompanied at the end by a completely linked layer and SoftMax layer.

All convolutional (All Conv) (Springenberg et al., 2014), LeNet (LeCun et al., 1998), AlexNet (Krizhevsky & Hinton, n.d.), NiN(Lin et al., 2013) and VGG Net (Simonyan & Zisserman, 2014) are some examples of such models.

Inception Units GoogleNet(Szegedy et al., 2015)(Szegedy et al., 2016) ResidualNetworks(He et al., 2016), Dense Net(Huang et al., 2017), and Fractal Net (Larsson et al., 2016) are the alternative and more powerful advanced architectures

Many DCNN due to their state-of-the-art success architecture, for various challenges for object recognition tasks, AlexNet, VGG, GoogLeNet, Fractal Net and Dense Net are considered the most common networks. Several of the networks are explicitly built for all these architectures for large-scale data processing like ResNet and GoogLeNet, while the VGG network is regarded a general network. In connectivity terms, some architectures, such as DenseNet, are complex. The Fractal Network is one alternative to ResNet.

In this research we used AlexNet to classify the images, therefore AlexNet is going to be discuss in details.

CHAPTER 3

METHODOLOGY

2.1 Dataset Description

Among the data collected are photos of houses in Nicosia, Northern Cyprus. In 2020, this data was collected containing 2184 images with an average image size of 256 x 256 pixels. The images are displayed in JPEG format. The data was split into five categories and each section has classes.

The first category is Villa versus Apartments class. The second category is split into two class namely 0 to 5 years old Apartments 6 to 10 years old Apartments. The third category is villa with roof versus Villa without roof apartments class. The fourth category is Villa Price from 10,000 euro to 200,000 Versus Villa Price from 200,000 Euro to above. The last category consists of three classes namely 2 floor Apartment versus 3 floor Apartment, 2 floor Apartment versus 4 floor Apartment and 2 floor Apartment versus 5 floor Apartment. The beginning of this work is dataset collection, all image was access from the popular Northern Cyprus real estate company 101 Elver. The company is known as the leading re al estate portal of Northern Cyprus. their mission is to create a platform where all properties for sale or rent in Cyprus are located, where buyers and sellers meet. All the images in the data set are collected from Nicosia Area of Northern Cyprus. The dataset can be access at www.101elver.com.

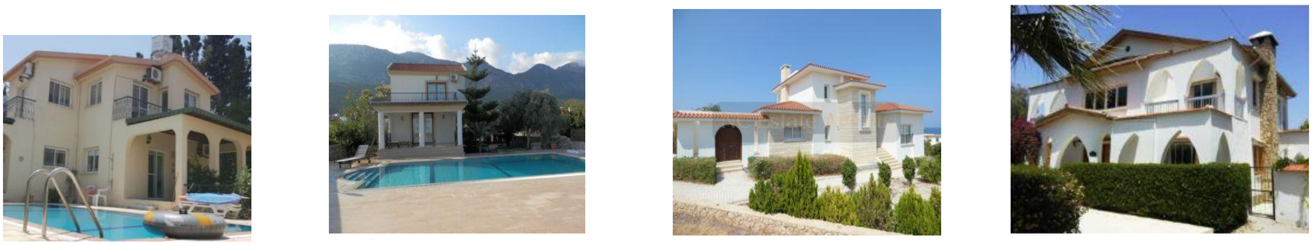
The images collected has different sizes, we resize the image using an online image resizer https://bulkresizephotos.com/en to suit our model. The Table 3.1 show the of classes of the houses and the number of images in each case.

Table 3.1: Classes of the houses and the number of images in each case

Class	**Number of images**	**Training Image**	**Testing Image**
Apartment	219	110	110
Villa	143	72	72
0-5 Years old Apartments	207	145	63
6-10 Years old apartments	145	101	44
Villa with roof	209	146	63
Villa without roof	195	137	59
Villa Price from 10,000 Euro to 200,000 Euro	206	144	62
Villa Price from 200,000 Euro to Above	301	211	90
Apartments with 2 floors	170	119	51
Apartments with 3 floors	151	106	45
Apartments with 4 floors	104	73	31
Apartments with 5 floors	132	92	40
Total	2182		

2.1.1 Sample of the original image dataset collected

(a) Apartment Houses

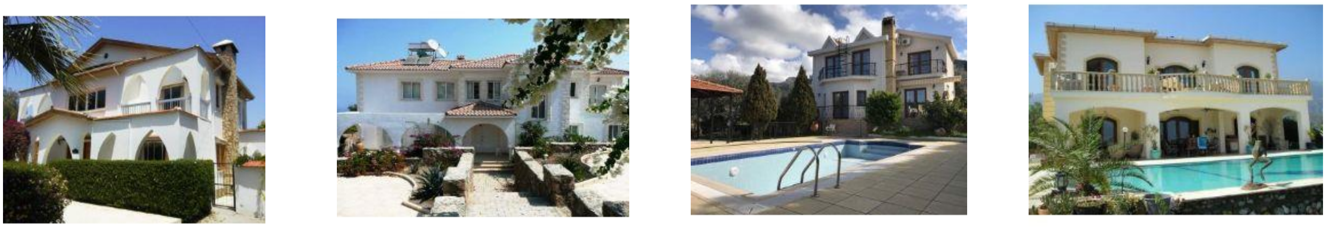


(b) Villa Houses

(c) 0-5 years Apartment

(d) 6-10 years Apartment

(e) Villa price 10,000 to 200,000 Euro



(f) Villa Price from 200,000 to above

(g) Villa with roof

(a) Villa without roof

(b) Apartment with 2 to 5 number of floors

Figure 3.1: Building Types in Northern Cyprus

2.2 Preprocessing

The dataset has been arranged five different categories each one contain sub folders of the classes to be classify. The name of each sub folder is the name of the class. To take care of data inadequacy, we used Data augmentation techniques. also, the method supplies the network with the required details of learning of training data and reduced the probability of overfitting. We have images of various sizes in the dataset, but the AlexNet architecture needs 256X256 input images. We have therefore changed the training and testing of images using online bulk resizer https://bulkresizephotos.com/en to render images appropriate for our network Some additional augmentation operations were added, such as randomly rotating the training images along the vertical axis and converting images up to 30 pixels in both vertically and horizontal. MATLAB's image Data Augmenter library has been used for all the preprocessing tasks, which have various sets of data pre - processing options, such as translation, reflection, scaling, rotation, scaling, augmentation and shearing have been used in the training results(Satone et al., 2017).

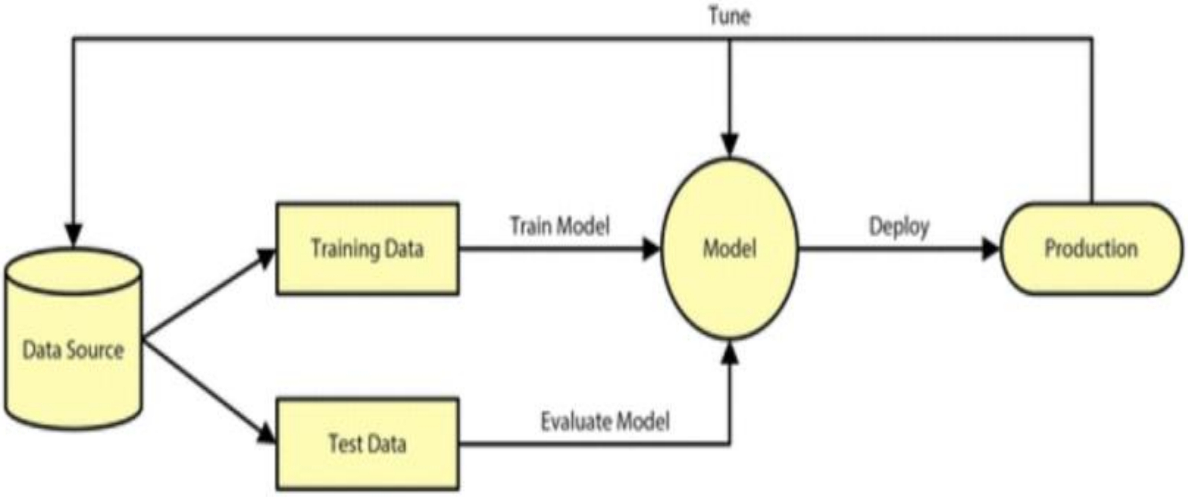


Figure 3.2: Proposed Method

2.3 AlexNet

Against all traditional ML methods, It was an exciting development for object identification and classification tasks in the field of ML (Krizhevsky & Hinton, n.d.). Compared to LeNet, Alexnet is more advanced and wider.

Our network architecture is described in the figure below. It comprises eight layers that have been learned, five that are convolutional and three that are fully connected. Some of the new or unique features of the architecture of our network are listed below.

The first five is convolutional layer and the remaining three are completely connected. Convolution and Max-Pooling with LRN (Local Response Normalization) are done by the first convolutional layer, in which ninety-six 11 x 11 in size different receptive filters are used.

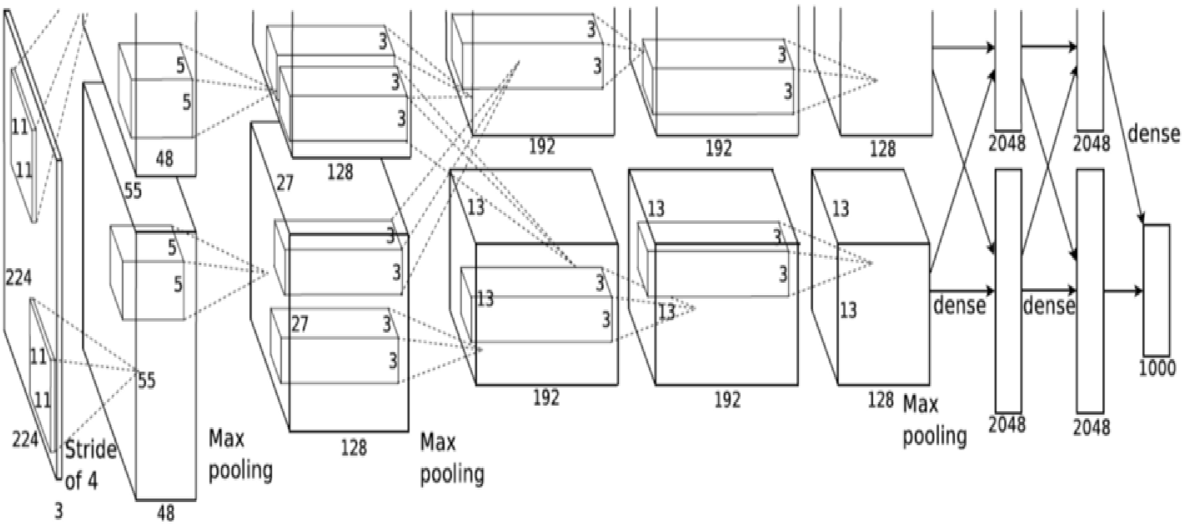


Figure 3.3: AlexNet Architecture(Mashrur, 2019)

2.4 Alexnet Layers

The 2nd,4th and 5th convolution layer kernels are only linked to the kernel maps on the preceding layer that are on the same GPU. The 3rd convolution layer kernels are linked to kernel maps on 2nd layer.

Max-pooling layers follow all feedback layers in the preceding layer and the 5th convolutional layer is linked to all neurons by the neurons in the fully connected layers. The ReLU is added to the output of fully-connected and convolutional layer.

An input image is filtered by the 1st convolutional layer of 224x224x3 with ninety-six kernels with size with a distance between adjacent neurons' receptive field centers of 4-pixel kernel map.

The 2nd convolutional layer takes output of the first convolutional layer as input and filters it with 256 kernels of 5 x 5 x 48 size. Without any interference of pooling or normalization layer, 3rd,4th and 5th convolutional layers are related.

and the 5th convolutional layer of size 3 x 3 x 192 has 256 kernels. Which makes the fully-connected layers to have the total of 4096 neurons each.

2.4.1 Rectified Linear Unit Nonlinearity

The method for modeling a neuron's output as a function of its input that is most commonly used. In terms of training time using gradient descent, these saturating nonlinearities are significantly slower than non-saturating nonlinearities. Neurons with this nonlinearity are known as Rectified Linear Units (ReLUs). Deep CNNs using ReLUs learn much faster than those using tanh units.

2.4.2 Training on multiple GPUs

The largest size of networks that can be trained on a single GTX 580 GPU is limited because it only has 3GB of memory. It turns out that 1.2 million training samples are enough to train networks that are too big for a single GPU to handle. As a result, the network was split between two GPUs. Because they can read and write to each other's memory without passing via the host machine's memory, today's GPUs are especially well-suited to cross-GPU parallelization. With one exception: the GPUs only communicate in specific levels, we employ a parallelization approach that simply places half of the kernels (or neurons) on each GPU. This strategy reduces our error rates when compared to a net with half as many kernels in each convolutional layer trained on a single GPU. A two-GPU net requires somewhat less time to train than a one-GPU net.

2.4.3 Local response normalization(ReLu)

The advantage of ReLUs is that they don't require input normalization to avoid saturation. If at least some training instances produce a positive input to the ReLU, that neuron will learn. The following local normalizing method, on the other hand, encourages generalization. The activity of a neuron is represented by x, y, which is calculated by first applying the kernel at (x, y) and then applying the ReLU nonlinearity.

2.4.4 Overlapping pooling

Pooling layers in CNNs summarize the outputs of neighboring clusters of neurons in the same kernel map. Traditionally, the neighborhoods summarized by nearby pooling units did not overlap. To be more exact, a pooling layer can be thought of as a grid of pooling units spaced s pixels apart that produces output with the same dimensions. We notice that models with overlapping pooling are marginally more difficult to overfit during training.

2.5 Data Augmentation Techniques

Data augmentation is a term used in data analysis to describe methods for enhancing the quantity of data available by adding slightly modified copies of existing data or developing new synthetic data from existing data. It acts as a regularizer when training a machine learning model, reducing overfitting. It is closely related to data analysis oversampling.

There are two sections to the network during the training phase(Krizhevsky & Hinton, n.d.). The augmentation network accepts two images from the same class as the input image and outputs a single layer. This layer is handled as if it were a "augmented" image. The augmented image is then sent to the second network, along with the original input image, the network of classification(Niblack, 1986).

The classification loss at the network's end is a cross entropy loss on the sigmoids of the class scores. An addition loss is computed at the end of the augmentation network to control how similar the augmented image should be to the input image.

The weighted sum of these two losses is used to compute the total loss.

Image translations and horizontal reflections were generated as part of the data augmentation process. We accomplish this by extracting random images from the image dataset and using these photos to train our network.

The size of our training set grows as a result, albeit the training instances that result are highly interdependent.

Our network would have suffered from significant overfitting without this method, forcing us to employ considerably smaller networks.(Krizhevsky & Hinton, n.d.).

2.6 Hyper Parameters

2.6.1 Learning Rate

The learning rate is a hyper parameter that determines how much the model changes when the weights are updated in response to the expected mistake. A value that is too little may cause the training process to be delayed and halted, while a value that is too big may cause the user to learn a sub-optimal set of weights too quickly or for the training process to be unstable.

When designing a neural network, the learning rate may be the most critical hyper parameter to consider. As a result, it's critical to understand how to examine the effects of the learning rate on model performance and to build an intuition for the learning rate's dynamics on model behavior.(Azadeh et al., 2009).

It also has an effect on how quickly the model adapts to changing conditions. Due to the smaller increases in the weights each update, lower learning rates necessitate more training epochs, but higher learning rates necessitate fewer training epochs due to the learning rate being adjustable with a modest positive value.

It's possible to employ a simple or weighted learning rate. A model with a high learning rate may converge too fast to a suboptimal solution, whereas a model with a low learning rate may halt the process.

2.6.2 Epoch

An epoch is a unit of time used to train a neural network for a single cycle with all of the training data. In an epoch, we use all of the data exactly once. One pass is made up of a forward and backward pass. It normally takes several epochs to train a neural network(Khare & Nagwanshi, 2011). To put it differently, if we feed a neural network training data in a variety of patterns throughout multiple epochs, we can expect better generalization when we give it new data. An epoch consists of one or more batches in which the neural network is trained on a subset of the dataset.

2.6.3 Iteration

Iteration refers to the number of batches or steps required to complete one epoch through partitioned packets of training data. We have numerous iterations for each full epoch. You completed one iteration each time you passed a batch of data through the neural network.

In neural networks, this refers to the forward and backward passes. As a result, iteration can be defined as a ratio of batch size to Epoch(Khare & Nagwanshi, 2011).

2.6.4 Batch Size

Batch size is another hyper parameter that we must test and tweak based on how our specific model performs during training. This parameter will also need to be examined to see how our system performs in terms of resource utilization when different batch sizes are used.

The batch size refers to the total number of samples that will be sent to the network at once. It's worth noting that a batch is also known as a mini-batch.

Our model will complete each epoch during training faster if the batch size is higher. This is due to the fact that, depending on our computational capacity, our system may be capable of processing much more than one single sample at each time. However, even if our machine can handle very big batches, the model's quality may deteriorate as we increase the batch size, and the model may eventually be unable to generalize adequately on data it hasn't seen before(Azadeh et al., 2009).

2.7 Learning Details

We train our first model (Villa Vs Apartment) with weighted learning rate of 25, basic learning rate of 25, minibatch size of 10, MaxEpochs of 100, Valid frequency 3.

We also used 50% of our data for training and 50% for Validation shown in table 3.2.

Table 3.2: Learning details for Villa Versus Apartment Class

Weighted Learning rate	Basic Learning rate	Minibatch Size	MaxEpoch	Valid Frequency	Training data%	Testing Data%
25	25	10	100	3	50	50

For our 2nd Model (0-5 years old Vs 5-10 years old), we train our model with weighted learning rate of 10, mini batch size 10, MaxEpoch 100 and Valid frequency of 3. We used 70% of our data for training and 30% for validation as summarized in table 3.3.

Table 3.3: Learning details for 0-5 years old Vs 5-10 years Old Class

Weighted Learning rate	**Basic Learning rate**	**Minibatch Size**	**MaxEpoch**	**Valid Frequency**	**Training data%**	**Testing Data%**
10	10	10	100	3	70	30

For the remaining models (Villa with roof vs Villa without roof, Villa Price from 10,000 Euro to 200,000 Euro Vs Villa Price from 200,000 Euro to Above and 2 floor Apartments Vs 3,4and 5 floor Apartment) we train them with weighted learning rate of 20, mini batch size 20, MaxEpoch 100 and Valid frequency of 3. We used 70% of our data for training and 30% for validation as summarized in Table 3.4.

Table 3.4: Learning details for Villa with roof vs Villa without roof, Villa Price from 10,000 Euro to 200,000 Euro Vs Villa Price from 200,000 Euro to Above and 2 floor Apartments Vs 3,4and 5 floor Apartment classes

Weighted Learning rate	**Basic Learning rate**	**Minibatch Size**	**MaxEpoch**	**Valid Frequency**	**Training data%**	**Testing Data%**
20	20	20	100	3	70	30

For all the models, all the network parameters used was adjusted manually throughout training.

MATLAB Version 2019a was used for implementation. The network was developed on a personal computer with 7th Gen intel(R) Core i7-7500u and NVIDIA® GeForce 940MX SUPER GPU*1 MATLAB version R2019a was used

2.8 Performance Matrices

Accuracy is a data measure described as the proportion of data samples correctly classified from the result to all samples. Sensitivity & specificity similarly, are Statistical indicators that accurately forecast the percentage of Both the tests with positive data and a part of all the negative data samples respectively(Burkov, n.d.).

For of class of input images, True positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) result obtained may vary according to result obtained from the confusion matrix. If an apartment is forecast as an apartment, it shows a TP for that class. In contrast to this class, all the accurate predictions for other classes are referred to as TN. If an input image of an apartment is predicted as a villa, it is considered false positive.

All these can be obtained using the following equations:

$$Sensitivity = \frac{TP}{TP + TN} \tag{3.1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3.2}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{3.3}$$

$$Precission\ factor = \frac{TP}{TP + FP} \tag{3.4}$$

In a nut shell Sensitivity tests the proportion of accurately labelled data correctly classify to the overall data correctly identified as positive Classification. Specificity tests how good the other groups are estimated by the algorithm. Accuracy tests the overall accuracy of the algorithm 's classification rate.

CHAPTER 4

RESULT AND DISCUSSION

3.1 Villa and Apartments Class

Transfer learning with pre-trained AlexNet was used in the system proposed. From the result we obtained, we can believe that the result achieved by the proposed approach where the Villa Vs Apartment class is precisely classified.

The accuracy overall achieved is 96.40% as shown from the figure below, we can see that the values of other metrics are Sensitivity is 98.17%, Specificity is 97.36%, Prevalence is 98.20% Positive Predicted Value is 98.37% and Negative Predicted Value is 96.21%. The result is summarized in table 4.1.

The training cycle parameters are also recorded such as Epoch, number of iteration and iteration per Epoch and validation frequency as shown in the figure 4.1.

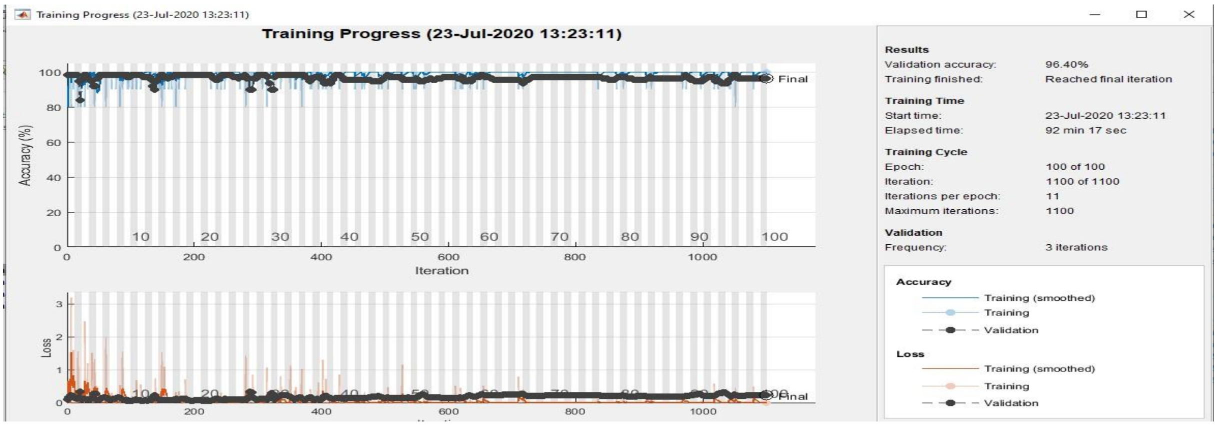


Figure 4.1: Villa and Apartments Class result

3.2 0-5 Years and 6-10 years (old) Apartments Class

On the basis of the results obtained, we may conclude that a good success was achieved by the proposed approach where the classification of 0-5 Years Vs 6-10 years' age Apartments Class is 87.42% accurate as we shown from the figure below. we can see that the values of other metrics are Sensitivity is 85.29%, Specificity is 80.68%, Prevalence is 89.20% Positive Predicted Value is 88.17% and Negative Predicted Value is 81.67%. The result is summarized in table 4.1

The training cycle parameters are also recorded such as Epoch, number of iteration and iteration per Epoch and validation frequency as also recorded.

3.3 Villa with roof and Villa without roof class

The accuracy overall achieved is 87.60% as shown from the figure below, we can see that the values of other metrics are Sensitivity is 93.65%, Specificity is 81.03%, Prevalence is 59.21% Positive Predicted Value is 82% and Negative Predicted Value is 82.96%. The result is summarized in table 4.1.

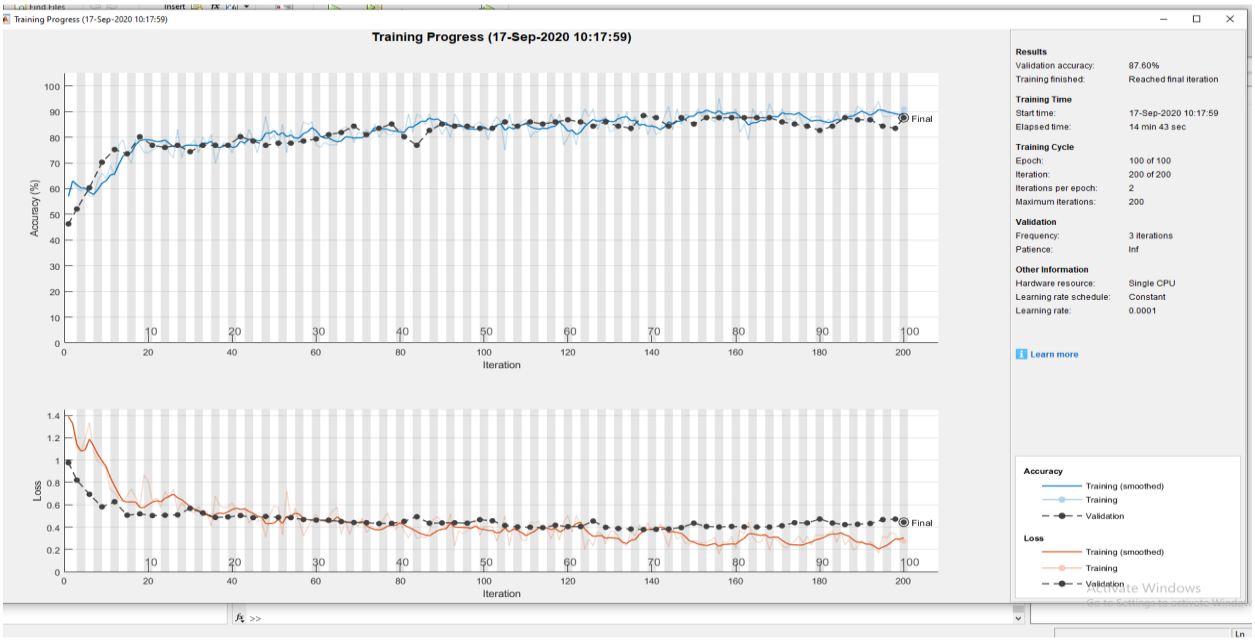


Figure 4.2: Villa With roof and Villa without roof class result

3.4 Villa Price Class

The accuracy achieved as was 81.84%. The values of other metrics are sensitivity of 85.56% which shows the proportion of accurately labelled data correctly identified to the overall number of data correctly identified as positive is not is reliable.

The value of specificity is recorded at 85.48% which is good performance. 59.29%, 52.96% and 82% for prevalence, positive predicted value and Negative Predicted Value respectively. the result is summarized in table 4.1.

On the basis of the results obtained, the proposed method is need to be improve.

3.5 2 floor and 3 floor Apartment Class

The overall accuracy achieved was 83.84%. The values of other metrics are sensitivity of 84.31% which shows the result of the proportion of accurately labelled data correctly identified to the overall number of data correctly identified as positive is good.

The value of specificity is recorded at 40%. The result shows how the other groups are estimated by the algorithm is not good. 53.13%, 69.23% and 61.43% for prevalence, positive predicted value and Negative Predicted Value respectively. the result is summarized in table below.

On the basis of the results obtained, the proposed method is need to be improve.

3.6 2 floor and 4 floor Apartment class

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Based on the result obtained, we may conclude that a great result was achieved by the proposed approach where the 2 floor and 4 floor Apartment class is precisely classified.

Overall accuracy was 82.48%. The values of other metrics are 89.41% for sensitivity, 71.15% for Specificity, 62.04% for prevalence, 80.43% for positive predicted value and 83.52% for Negative Predicted Value. the result is summarized in table 4.1.

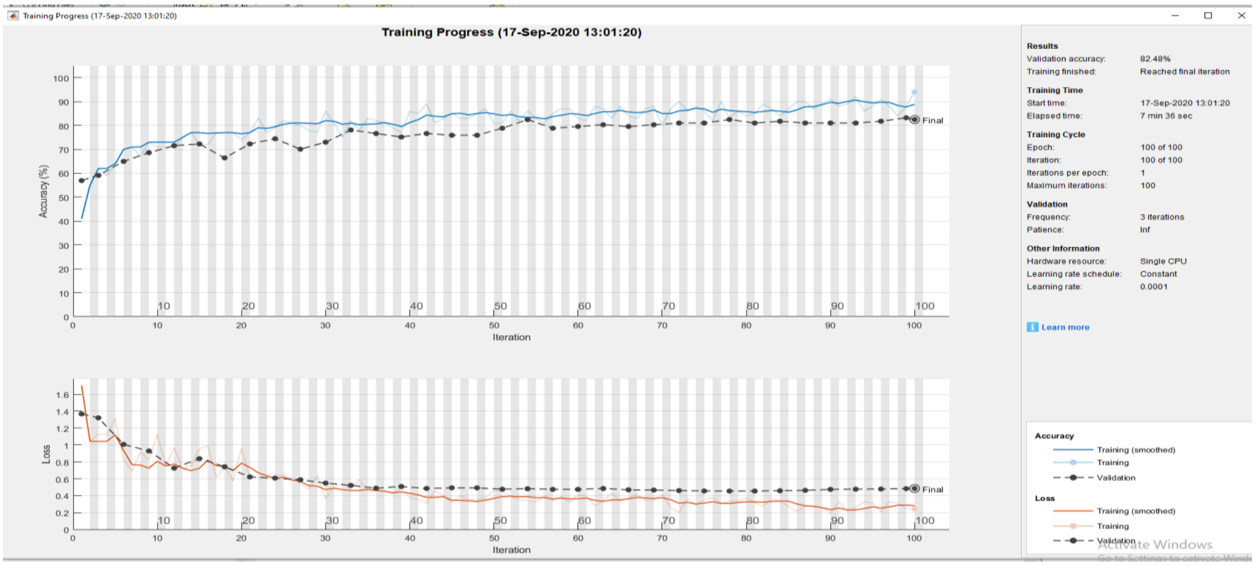

Figure 4.3: 2 floors Versus 4 floor Apartment class result

3.7 2 floor and 5 floor Apartments Class

The accuracy was recorded at 84.77%. The values of other metrics are 87.06% for sensitivity, 81.82% for specificity, 56.29% for prevalence, 83.08% for positive predicted value and 86.05. the result is summarized in table 4.1.

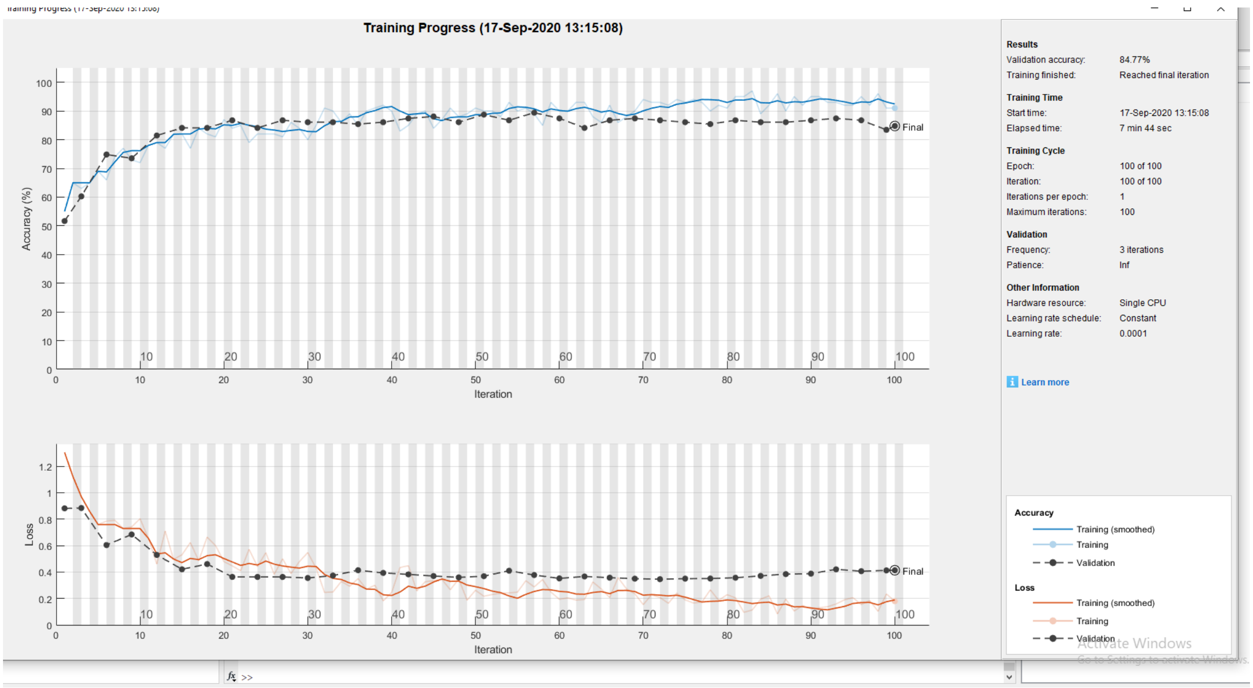

Figure 4.4: 2 floors Versus 5 floor Apartment class result

Table 4.1: Table of result

Dataset	Class	Predictive Positive Value	Predictive Negative Value	Prevalence	Accuracy %	Sensitivity %	Specificity %
Category One	Apartments Villa	0.9837	0.9621	0.9820	96.40	98.17	97.36
Category Two	0-5 Years apartments Vs 6-10 Years Apartments	0.8817	0.8167	0.8920	87.42	85.29	80.68
Category Three	Villa with roof Vs Villa without roof	0.8429	0.9216	0.5207	87.60	93.65	81.03
Category Four	Villa Price from 10,000 euro to 200,000 Vs Villa Price from 200,000 Euro to above	0.8200	0.5296	0.5929	81.84	45.56	85.48
Category Five	2 floor Vs 3 floor Apartments	0.6143	0.6923	0.5313	83.54	84.31	40.00
	2 floor Vs 4 floor Apartment	0.8352	0.8043	0.6204	82.48	89.41	71.15
	2 floor Vs 5 floor Apartment	0.8605	0.8308	0.5629	84.77	87.06	81.82

CHAPTER 5

CONCLUSION AND RECOMENDATIONS

In this thesis, we review Artificial Neural Networks, its working principles and training algorithm such as back propagation learning techniques. Deep learning was discussed which include deep learning approaches such supervised learning, semi-supervised, un-supervised and reinforcement learning. Convolutional neural network has a significant effect on image classification, that makes it suitable candidate to use in this research.

After study and implementation of deep learning in the field of house classification it is concluded that deep leaning while using AlexNet provide very good result. First these images were downloaded from 101elever, a leading real estate company in Cyprus and the image is resized to fit our network.

The dataset has been arranged in five different categories each one contain sub folders of the classes to be classify. Being it supervised learning, the name of each sub folder is the name of the class. To solve the problem of in availability of the data, we used Data augmentation techniques(Satone et al., 2017). also, the method helps the system with all necessary details of training data and reduced the probability of overfitting. We have images of various sizes in the dataset, but the AlexNet architecture needs 256X256 input images.

The first category is Villa versus Apartments class, based on the training dataset of 362 images the class result shows the overall accuracy of 96.40%. this show that villa vs apartment class has been very well classified. The second category is split into two class namely 0 to 5 years Apartments 6 to 10 years Apartments. This class is to classified the building based on their age and the result shows the accuracy of 87.42%.

The third category is villa with roof versus Villa without roof apartments class which also shows the overall accuracy of 87.60%. The fourth category is Villa Price from 10,000 euro to 200,000 Versus Villa Price from 200,000 Euro to above and the result shows the accuracy of 81.84%. The last category consists of three classes namely 2 floor Apartment versus 3 floor Apartment, 2 floor Apartment versus 4 floor Apartment and 2 floor Apartment versus 5 floor Apartment which all shows the accuracy of 83.54%, 82.48% and 84.77% respectively.

From the experiments carried out in this thesis and the results obtained we conclude that the main aims and objectives of this thesis which is to used Deep learning in Classification and detection of houses in Northern Cyprus and to test the performance of AlexNet for houses classification was achieved.

This study will be very significant in creation of smart cities and digitization of real estate sector as the world embrace the used of the vast power of Artificial Intelligence, machine learning and machine vision.

Future work will focus on the extension of building types classes and on the consideration of additional or more differentiated infrastructural features such villa versus bungalow, house with swimming pool and house without swimming pool, more precise building age, more detail building price, and so on.

Also, for the CNN architecture, we can test our proposed networks using other CNN architecture like ResNet, GoogleNet and DenseNet

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